

Here b denote sites, there are B sites in total.
 d denote detector tube and there are D tubes in total.
 $P(b, d)$ is the probability that emission in b is detected in tube d . The emission at site b is assumed to be poisson with mean $\lambda(b)$

$n^*(d)$ is the total number of emission detected in tube d during acquisition (real data)

$n(b, d)$ denote the number of emission in b detected in d .
 $n(b, d)$ are mutually independent poisson random variable, across b , across d . (Split of poisson process independent)

$n(b, d) \sim \text{Poisson}(\lambda(b, d))$

$$\sum_{d=1}^D P(b, d) = 1$$

$$\lambda(b, d) = \lambda(b) \times P(b, d)$$

$$n^*(d) = \sum_{b=1}^B n(b, d) \Rightarrow \lambda^*(d) = E[n^*(d)] = \sum_{b=1}^B \lambda(b) P(b, d)$$

\Rightarrow Best estimate of $\lambda^*(d) = n^*(d)$

$$\Rightarrow n^*(d) = \sum_{b=1}^B \lambda(b) P(b, d) \quad \text{for } d=1, \dots, D.$$

Above set of linear equations form the basis for inversion reconstruction.

Now let's move on to expectation maximisation. If we have $n(b, d)$ as hidden random variable then, estimation of $\lambda(b)$ becomes very easy.

So $x =$ Hidden Random Variable $= n(b, d)$

$y =$ observed data $= n^*(d)$

$$\text{Likelihood} = P(x, y) = \prod_{b=1}^B \prod_{d=1}^D e^{-\lambda(b, d)} \frac{(\lambda(b, d))^{n(b, d)}}{n(b, d)!} \quad (\because \text{each } n(b, d) \text{ poisson process is independent})$$

$$\left(\sum_{b=1}^B n(b, d) = n^*(d) \quad \forall d \right)$$

$$\log \text{likelihood} = \sum_{d=1}^D \sum_{b=1}^B -\lambda(b, d) + n(b, d) \log(\lambda(b, d)) - \log(n(b, d)!) \quad \uparrow \text{ of no use as does not contain parameter } \lambda(b, d)$$

$$E[n(b, d) / n^*(d)] = \frac{n^*(d) \dot{\lambda}(b, d)}{\sum_{b'=1}^B \dot{\lambda}(b', d)} \quad \dot{\lambda}(b, d) = \text{estimate at } i^{\text{th}} \text{ iteration}$$

$$\Rightarrow E[\log \text{likelihood}] = \sum_{d=1}^D \sum_{b=1}^B -\lambda(b, d) + \frac{n^*(d) \dot{\lambda}(b, d)}{\sum_{b'=1}^B \dot{\lambda}(b', d)} \log(\lambda(b, d)) = Q(\theta, \theta^i)$$

Differentiating above with respect to $\lambda(b, d)$ to get maxima

$$\Rightarrow \lambda^{i+1}(b, d) = \frac{n^*(d) \dot{\lambda}(b, d)}{\sum_{b'=1}^B \dot{\lambda}(b', d)} \quad \dot{\lambda}(b, d) = \dot{\lambda}(b) P(b, d)$$

$$\lambda(b) = \sum_{d=1}^D \lambda(b, d)$$

$$\Rightarrow \lambda^{\text{new}}(b) = \frac{\text{old } \lambda(b) \sum_{d=1}^D \frac{n^*(d) P(b, d)}{\sum_{b'=1}^B \hat{\lambda}_{\text{old}}(b') P(b', d)}}{\sum_{d=1}^D \frac{n^*(d) P(b, d)}{\sum_{b'=1}^B \hat{\lambda}_{\text{old}}(b') P(b', d)}}$$

Final formula for update is given below

$$\lambda^{\text{new}}(b) = \frac{\text{old } \lambda(b) \sum_{d=1}^D \frac{n^*(d) P(b, d)}{\sum_{b'=1}^B \hat{\lambda}_{\text{old}}(b') P(b', d)}}{\sum_{d=1}^D \frac{n^*(d) P(b, d)}{\sum_{b'=1}^B \hat{\lambda}_{\text{old}}(b') P(b', d)}}$$